IJCTA, 9(10), 2016, pp. 4623-4630

Impact of Least square Denoising on Kernel Based Hyperspectral Image Classification

*** Megha.P, Swarna.M, Deepa Merlin Dixon.K **V.Sowmya, KP Soman**

Abstract : Hyperspectral sensors capture images in hundreds of spectral bands spanning almost all the regions in the electromagnetic spectrum. These images consists of many noisy bands. Hence, a strong diffusion scheme (denoising) is required to extract the meaningful spatial information present in the noisy spectral bands. In this paper, one dimensional signal denoising based on weighted regularized least square (LS) method is mapped to two dimensional hyperspectral image (HSI) denoising and the superiority of this method is determined on the basis of the classification accuracies of the hyperspectral image obtained using Grand Unified Regularized Least Square (GURLS) library and LibSVM, the support vector machines library. The proposed method brings out the efficiency of LS denoising based on the classification accuracies obtained on classifying the denoised image. The obtained results are also compared with the accuracy obtained on classifying the original image without denoising. The analysis is also extended to the classification of the images denoised using the conventional denoising techniques such as Total Variation (TV) and LF (Legendre Fenchel) based denoising. From the analysis, it is observed that the classification accuracies of the images denoised using the proposed method is much higher than the conventional denoising methods. Hence, showing that the LS based denoising is an efficient method which provides a denoised output almost similar to the original image.

Keywords : Hyperspectral Image; Least Square denoising; Legendre Fenchel denoising; kernal methods; LIBSVM; GURLS.

1. INTRODUCTION

In remote sensing, we exploit the fact that various objects on the surface of earth reflect, absorb and emit electromagnetic radiation at different wavelengths [1, 2]. With the recent development in hyperspectral imaging, remote sensing field has stepped into a new era of image acquisition. Hyperspectral sensors capture images simultaneously in hundreds of narrow spectral bands, which helps us to detect and identify different objects on the earth's surface [1]. The continuous spectrum of each image cell gives an explicit information of the scene being captured. But, the effective use of hyperspectral image relies upon the processing techniques along with human interpretation and analysis of image data [2,3].

In this paper, least square denoising method is proposed as a preprocessing step for hyperspectral image classification. Remote sensing images are highly prone to different types of noises, which adversely affects the information extraction from the image [4]. So, the first and foremost step in image analysis is to eliminate the contaminated components from the obtained data. Conventional denoising techniques include Total Variation (TV), wavelet and Legendre Fenchel (LF) denoising [1]. The goal of these existing techniques is to estimate denoised

* Center for Computational Engineering and Networking, Amrita School of Engineering, Coimbatore Amrita Vishwa Vidyapeetham, Amrita University, India meghaparakatt@gmail.com, swarna9693@gmail.com, deepamerlin123@gmail.com

** Center for Computational Engineering and Networking Amrita School of Engineering, Coimbatore Amrita Vishwa Vidyapeetham, Amrita University, India v_sowmya@cb.amrita.edu, kp_soman@amrita.edu

image from noisy image. But, the major drawback of the existing method is high computational time and mathematical complexity [1]. In this work, we focus on least square based denoising technique which has low mathematical complexity and takes less computational time compared to the existing techniques. Classification of hyperspectral image is a challenging task because of its high dimension [1,3]. In this paper, Grand Unified Regularized Least Squares (GURLS) and LibSVM packages are used for efficient classification of the denoised hyperspectral image and the accuracies obtained are compared with the classification accuracies obtained before denoising to project the efficiency of the least square denoising technique.

2 CLASSIFICATION TECHNIQUES USED

In this section, Support Vector Machine (SVM) and Regularized Least Square (RLS), the two kernel based classification techniques used in this paper are explained briefly.

A. Support Vector Machine (SVM)

SVM belongs to a class of supervised learning algorithms in which the system is given a set of examples with labels [5]. It constructs a hyper plane that separates the data belonging to different classes. The algorithm tries to achieve maximum separation between the classes which ensures that chances of occurrence of an error reduces when a new sample is provided[5].

The SVM problem formulation in matrix format is given as :

$$\min_{w,\xi} \frac{1}{2} w^T w \tag{1}$$

subject to :$D[Xw - ye] \geq e$

where, D is a diagonal matrix of size $m \times m$ with class labels present as the diagonal elements, X is the data matrix of size $m \times n$, e is $a\ m \times 1$ column vector of ones and $\gamma \in R$. The data points used for classification through SVM can be linear or nonlinear.

Kernels are used in SVM to overcome the non-linearity problem in classification. In case of non-linear classification, the data is mapped to a space of higher dimension using the mapping function ψ where, ψ maps R^N to R^K given $K > N^5$.

LibSVM is a kernel based software library which classifies data using the multiclass SVM approach. For a multiclass problem, many binary classifiers are constructed using the one against one or one against all technique. In LibSVM, one against one method is used to generate $z(z\text{-}1)/z$ binary classes for a z class problem [6].

B. Regularized Least Square (RLS)

The Regularized Least Square approach aims at minimizing the L2 norm of the error and thereby calculating the weight matrix. This weight matrix is further used for predicting the labels of the testing samples. Consider a training set with training samples $(x_1, x_2, \ldots\ldots, x_n)$ and training labels $(y_1, y_2, \ldots.. y_n)$ where $x_i \in R^d$ $y_i \in (1,2,\ldots,T)$ for $i = 1, 2, \ldots..n$. Y is an $n \times T$ output matrix with $Y_{ij} = 1$ if i^{th} training sample belongs to j^{th} class and -1 otherwise. The optimization problem for a linear model is formulated as:

$$\min_{W \in R^{d \times T}} \left\{ \frac{1}{n} ||Y - XW||_F^2 + \lambda ||W||_F^2 \right\} \tag{2}$$

$$\min_{C \in R^{n \times T}} \left\{ \frac{1}{n} ||Y - KC||_F^2 + \lambda C^T KC \right\} \tag{3}$$

where, $||\,.\,||_F$ is the frobenius norm, K is a $n \times n$ matrix which includes kernel functions, Y is the vector which contains training labels and X is the vector which contains training samples. Optimal value of C is used for the prediction of class label. GURLS is a software library which utilizes regularized least square approach for classification [6,7].

3. PROPOSED METHOD

A. Least Square Denoising

In this section, the least square weighted regularization based denoising algorithm which is used for the band wise preprocessing of the HSI is discussed as shown in Fig.1. The one dimensional signal denoising approach using least square was proposed by Ivan.W.Selesnick [8]. In this paper, the one dimensional least square approach is extended to the two dimensional hyperspectral image denoising. The problem formulation for one dimensional signal denoising is given by

$$\min \| Y - X\|_2^2 + \lambda \| DX \|_2^2 \tag{4}$$

where, D is the second order difference matrix

$$D = \begin{bmatrix} 1-2\,1 \\ 1-2\,1 \\ \cdots \\ \cdots \\ 1-2\,1 \end{bmatrix}$$

In the formulation represented in eqn.4, 'Y' is a noisy hyperspectral band and 'X' is the denoised band. The basic idea behind this formulation is to obtain the denoised image 'X' on passing the noisy image 'Y' as the input. The process of denoising happens in the first part of eqn.2 and the second term corresponds to the regularization process which depends on the given value of λ. The minimization of the first term in the objective function in eqn.4 forces the output to be same as the input and the minimization of the second term leads to the smoothing of the noisy input thus, producing a denoised output signal. The role of the regularization parameter *ë*is to increase the extent of denoising as the noise level in the signal increases which is depicted in the least square formulation for signal denoising given by:

$$X = (I + \lambda D^T D)^{-1} Y \tag{5}$$

Where, I is the identity matrix.

B. Mapping of 1-D Least Square Denoising to 2-D HSI

The proposed method describes the efficiency of the least square based denoising through SVM based classification using LIBSVM and GURLS packages for polynomial kernel ($t = 1$), $C = 10^6$, gamma (g) = 0.9 and $\lambda = 2$. In order to show the effectiveness of the proposed method (classification of Indian Pines data-set preprocessed using least square based denoising), experimentation is carried out on the Indian Pines dataset (AVIRIS system captured dataset). This dataset consists of 240 spectral bands out of which 104-108, 150-163, 220 are the water absorption bands which are considered to be noisy [6], hence removed before any of the preprocessing steps. Excluding these, the rest 200 bands are used to carry out the experiment. The proposed method consists of the denoising and classification stages as shown in Fig.2.

The HSI (Indian Pines) is obtained over various spectral bands where, each spectral band is affected by different levels of noise. Thus, reducing the signal to noise ratio in turn leads to increase in the class error rate [1,6]. Therefore, in the preprocessing stage, band wise denoising is carried out using the least square denoising approach to obtain a better classification accuracy.

The 1-D least square denoising is mapped to 2-D by processing the HSI row wise and then column wise as shown in Fig.1. The row and column information is considered as a vector at each processing step.

Least square based denoising provides an advantage of less time consumption and easy implementation. The efficiency of the proposed method is compared with the existing preprocessing methods such as total variation denoising (TV), Legendre Fenchel denoising (LF) and wavelet denoising [1].

The classification stage comprises of the separation of data into testing and training data sets excluding the background pixels. 10% of the data is chosen randomly to train the classifier and 90% is used for testing. To prove the superior performance of the proposed method of least square based denoising, the classification procedure is applied on the hyperspectral dataset before and after preprocessing (denoising) and is compared based on the classification accuracies. The classifier packages used in the proposed method are LibSVM and GURLS package

4. EXPERIMENTAL RESULT AND ANALYSIS

In this paper, to prove the extent of effectiveness of the proposed method, a comparative study with the previously existing preprocessing techniques such as TV (Total Variation), LF (Legendre-Fenchel) and wavelet based denoising is performed, whose classification accuracies are compared to the classification results obtained by the proposed method (LS based denoising). The results obtained for each of the above mentioned denoising algorithms and the proposed method is shown in Table 1, which projects that the proposed method outperforms the state of the art methods in terms of classification accuracy using LIBSVM and GURLS package for SVM (support vector machine) based classification.

From Table 1, it is noticed that the proposed method shows the highest improvement in all the accuracy measurement parameters using both LIBSVM and GURLS packages. The accuracies in Table 2 shows a drastic improvement before and after preprocessing using the least square algorithm. The results obtained by the proposed method for 10% of training data shows an improvement in kappa coefficient from 0.7420 to 0.9255, overall accuracy from 77.3777% to 94.1872% and average accuracy from 74.57% to 92.78% using the LIBSVM package, 0.7658 to 0.9511, 79.5358% to 95.7055% and 73.12% to 95.98% of improvement respectively using the GURLS package for classification of HSI image after preprocessing using the least square approach. Fig.3 shows that the proposed method takes a minimal time of 18.5074 seconds for computations unlike methods such as total variation, LF and wavelet denoising which takes a computation time of 48.8411 seconds, 56.1406 seconds and 28.2872 seconds respectively.

A comparison of the class wise accuracies obtained before and after preprocessing using the least square based denoising algorithm is also made. Each band is denoised using the least square algorithm. The least square based denoising is carried out for the high pass filter coefficients [1 -2 1] with regularization parameter (λ) equal to 2. Table 2 shows the comparison between the class wise accuracies obtained before and after preprocessing (Least Square denoising) using the LIBSVM and GURLS classifier packages, it is observed that after preprocessing using least square denoising technique, there is a considerable amount of improvement in accuracies in class 3, class 4, class 9, class 10, class 12 and class 15 for LIBSVM and GURLS package, hence providing a better overall accuracy for classification using the proposed LS denoising.

From Table 1 and Table 2, it can be inferred that the proposed method provides the best classification accuracies in case of both LIBSVM and GURLS package whereas, the existing techniques provide less improvement in classification accuracies when compared with that of the proposed method. Fig.4 shows the effect of least square based denoising on Indian Pines dataset and Fig.5 represents the classification maps obtained before and after least square based preprocessing for 10% training data.

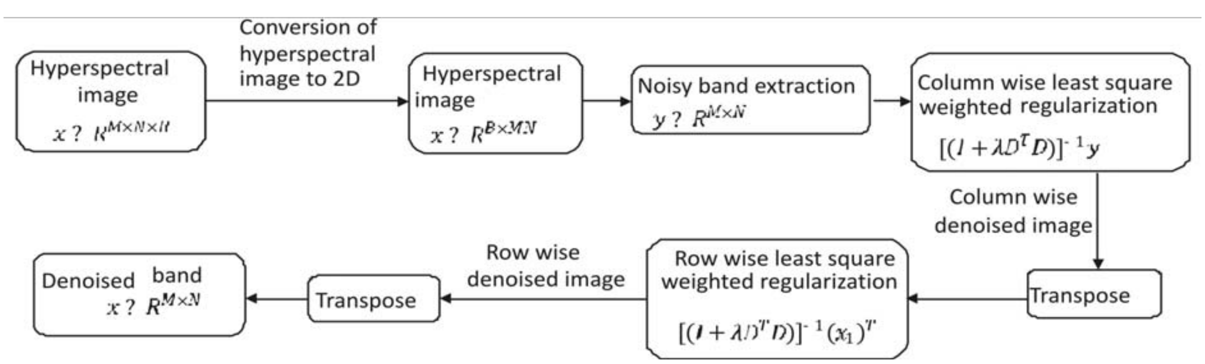

Fig. 1. Hyperspectral image denoising using Least Square approach (proposed method).

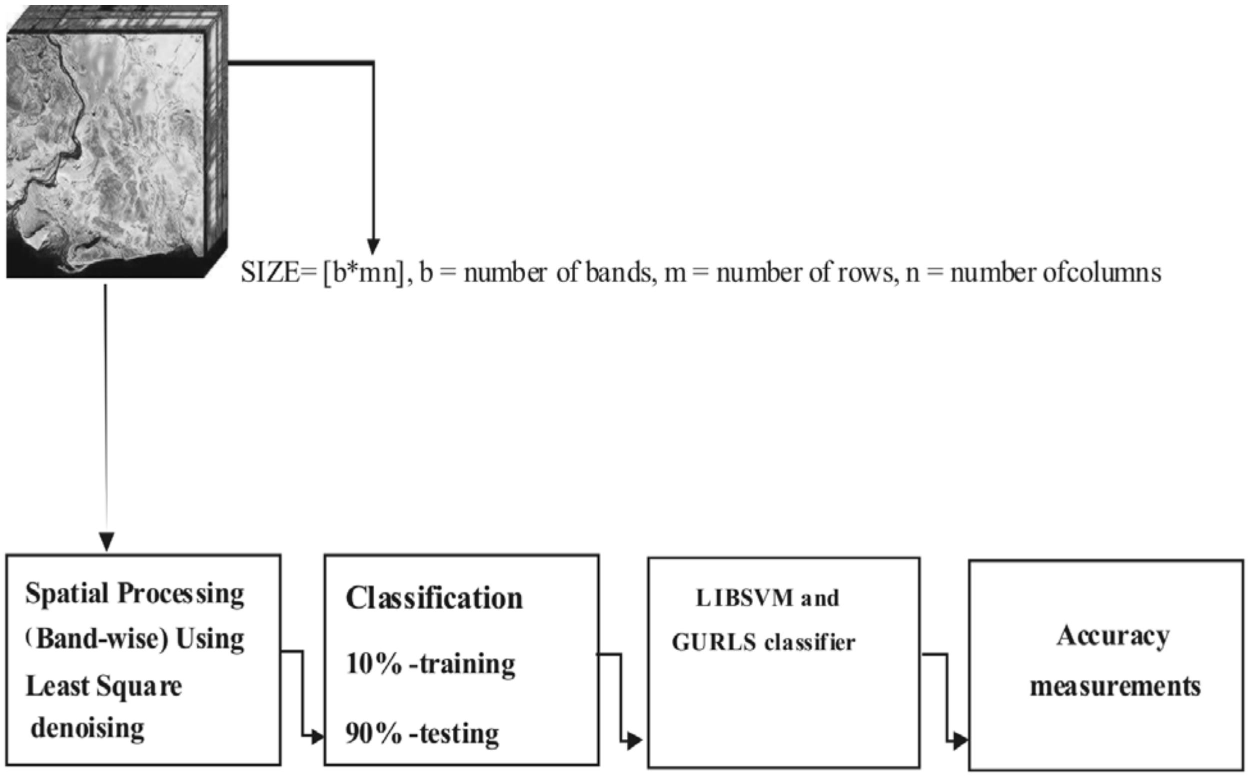

Fig. 2.Block diagram of the proposed method.

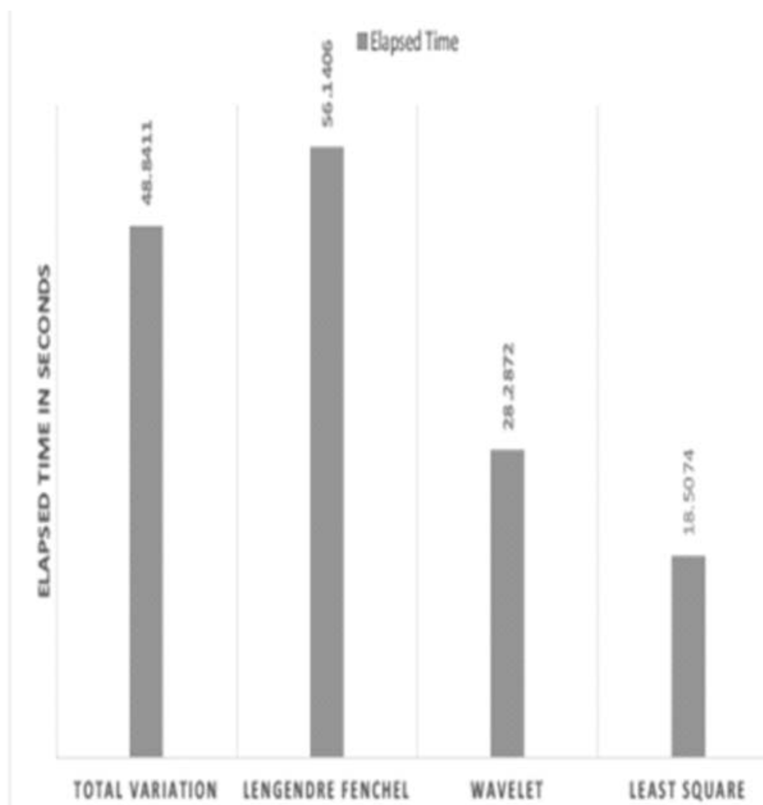

Fig. 3. Elapsed time analysis for different denoising methods on Indian Pines dataset.

Table 1. Comparative analysis of accuracy measurement parameters obtained before and after preprocessing usingLIBSVM and GURLS

Accuracy measurements	*Before preprocessing*		*LS Denoising*		*TV Denoising*		*LF Denoising*		*Wavelet Denoising*	
	LibSVM	*GURLS*	*LibSVM*	*GURLS*	*LibSVM*	*GURLS*	*LibSVM*	*GURLS*	*LibSVM*	*GURLS*
Overall Accuracy (%)	77.3777	79.5358	94.1872	95.7055	82.7242	85.7608	77.5729	81.6940	88.4394	90.7168
Average Accuracy (%)	74.57	73.12	**92.78**	**95.98**	82.95	84.58	75.54	76.22	92.78	89.15
Kapa	0.7420	0.7658	**0.9255**	**0.9511**	0.8029	0.8372	0.7440	0.7920	0.9255	0.8941

Table 2: Classwise accuracies obtained before and after preprocessing (Least Square) using LIBSVM and GURLS

CLASSES	*CLASSWISE ACCURACIES IN (%)*			
	LibSVM		*GURLS*	
	Before Preprocessing	*After Preprocessing*	*Before Preprocessing*	*After Preprocessing*
CLASS 1	78.05	90.24	63.41	97.56
CLASS 2	78.21	92.61	74.16	95.80
CLASS 3	**68.27**	**92.10**	**64.66**	**97.46**
CLASS 4	**46.01**	**86.35**	**48.83**	**97.18**
CLASS 5	91.26	93.10	86.67	97.93
CLASS 6	96.19	98.93	97.87	99.70
CLASS 7	92.00	100	32.00	100.00
CLASS 8	96.05	98.84	98.60	100.00
CLASS 9	**16.67**	**77.78**	**77.78**	**88.89**
CLASS 10	**67.54**	**89.71**	**74.29**	**91.09**
CLASS 11	74.65	93.03	81.17	94.52
CLASS 12	**63.48**	**91.39**	**67.23**	**92.88**
CLASS 13	98.91	97.28	98.37	99.46
CLASS 14	89.72	86.17	92.97	97.10
CLASS 15	**48.13**	**98.80**	**63.69**	**92.22**
CLASS 16	87.95	92.78	48.19	93.98

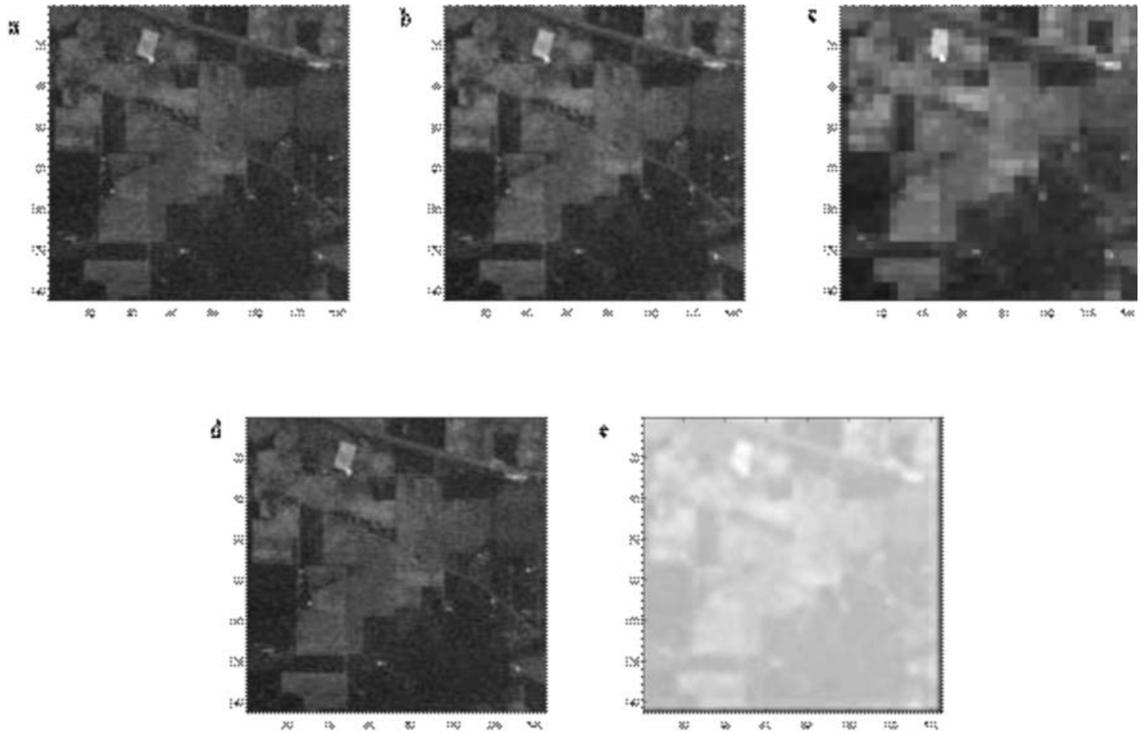

Fig. 4. Outputs obtained from different preprocessing methods, (*a*) Noisy Band 3 (*b*) TV denoised output (*c*) Wavelet denoised output (*d*) LF denoised output (*e*) LS denoised output (proposed method)

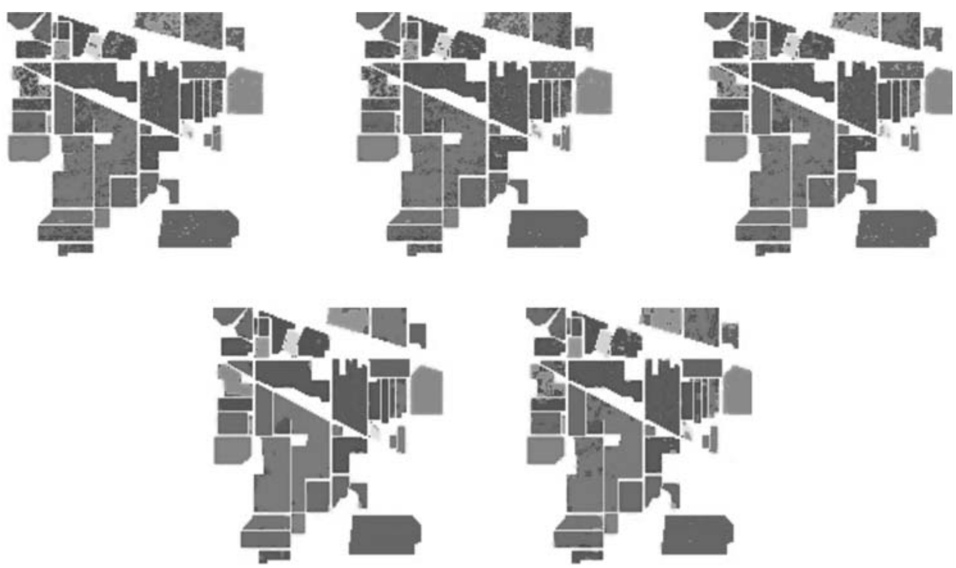

Fig. 5. Classification Maps obtained for different preprocessing methods, (*a*) Before preprocessing *(*b) LF (*c*) TV (*d*) LS (proposed method) (*e*) Wavelet

5. CONCLUSION

In this paper, the least square method is proposed as an effective technique for hyperspectral image denoising. The experiment is carried out on the Indian Pines data set and the effectiveness of the technique is proposed based on the accuracy measurement parameters like the overall accuracy, average accuracy, class wise accuracy and kappa coefficient. The band classification is implemented using the LIBSVM and GURLS package. From the experimental results obtained, it is evident that preprocessing of the hyperspectral image with least square denoising before classification has improved the quality of the image and hence, an improvement in the classification accuracy parameters is obtained when compared to the existing approaches for image denoising.

6. REFERENCE

1. C. Aswathy, V. Sowmya, R. Gandhiraj, and K. Soman, “Hyperspectral image denoising using legendrefenchel transformation for improved multinomial logistic regression based classification,” pp. 1670–1674, 2015.
2. G. Chen, T. D. Bui, K. G. Quach, and S.-E. Qian, “Denoising hyperspectral imagery using principal component analysis and block-matching 4d filtering,” *Canadian Journal of Remote Sensing*, vol. 40, no. 1, pp. 60–66, 2014.
3. A. C. Zelinski and V. K. Goyal, “Denoising hyperspectral imagery and recoveringjunk bands using wavelets and sparse approximation,” pp. 387–390, 2006.
4. C. Aswathy, V. Sowmya, and K. Soman, “Admm based hyperspectral image classification improved by denoising using legendrefenchel transformation,” *Indian Journal of Science and Technology*, vol. 8, no. 24, p. 1, 2015.
5. K. Soman, R. Loganathan, and V. Ajay, “Machine learning with svm and otherkernel methods,” 2009.
6. N. Haridas, V. Sowmya, and K. Soman, “Gurls vs libsvm: Performance comparisonof kernel methods for hyperspectral image classification,” *Indian Journal of Science and Technology*, vol. 8, no. 24, 2015.
7. A. Tacchetti, P. K. Mallapragada, M. Santoro, and L. Rosasco, “Gurls: a leastsquares library for supervisedlearning,” *The Journal of Machine Learning Research*, vol. 14, no. 1, pp. 3201–3205, 2013.
8. Selesnick, “Least squares with examples in signal processing,” *Online], March*, 2013.